PREDICTION OF ENERGY DEMAND AND AVAILABILITY TOWARDS STRATEGIC PLANNING OF ENERGY RESOURCES

A SYNOPSIS

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1. INTRODUCTION

Energy is essential to the modern world's ability to support and progress human life. All living things require it, permeating every part of our everyday lives. Energy is becoming a vital component of everyday life, as the modern revolution has highlighted its essential role. The modern civilization cannot exist without energy. It provides energy for our transportation networks, residences, businesses, and food production and delivery. The efficient operation of every industry significantly depends on a steady and dependable energy supply. The United States Energy Information Administration (EIA) released a study report that projects a 28% rise in worldwide energy use by 2040. Energy projections will influence energy conservation and ensuing energy policy, among other things [1].

The proportion of the Indian population connected to energy between 1990 and 2022 is shown in Figure 1. Getting electricity has increased over this period. Around sixty per cent of the individuals in the nation possessed electricity during 1990; the proportion stayed broadly consistent through the mid-1990s. The share rose steadily in 1996 and achieved almost 70% by 2004. The growth continued at the beginning of the twenty-first century, and after 2010, it gained substantial momentum. The percentage of people with access to energy will increase to roughly ninety per cent by 2022 [2]. This considerable rise over thirty years demonstrates the country's efforts and accomplishments in expanding its energy infrastructure and services. It also reflects improvements in energy laws, regulations, and technological innovations, particularly electrification-focused global assistance activities.

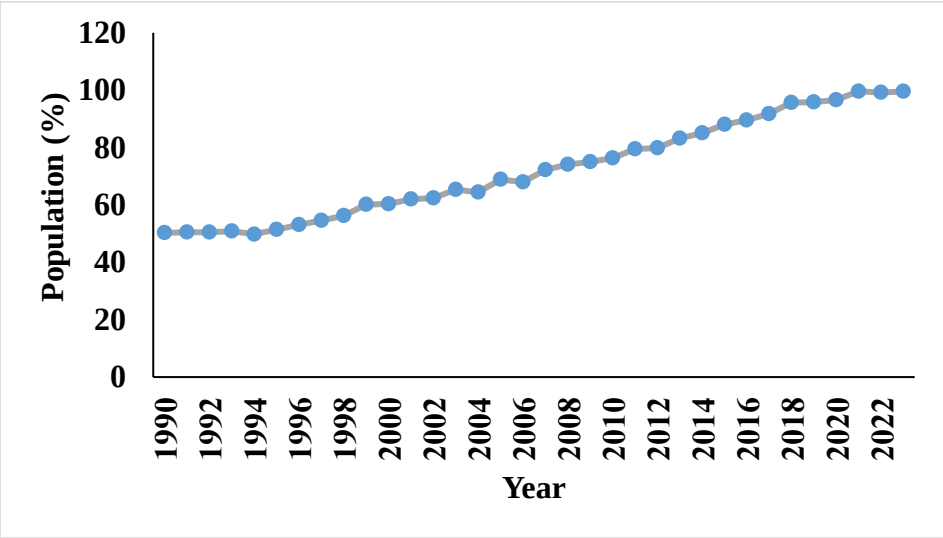

Figure 1: Access to electricity across Indian State

Residential buildings are among the most significant users of electricity. Based on research on energy utilization, forty per cent of the energy consumed worldwide is consumed in domestic regions. This category includes the electrical power used in houses for equipment, illumination, heat, and conditioning. Energy-efficient strategies and environmentally friendly energy sources are crucial to reduce the impact on the planet and guarantee the long-term security of electricity, as demonstrated by the significant proportion of the energy consumed in this domain.

Factories are an additional primary energy user. This sector incorporates mineral extraction, building, production, and other business operations that need a lot of electrical power to run manufacturing processes, manage buildings, and operate machines. Power is essential to industry productivity and financial sustainability. In addition to improving efficiency in operation, adequate energy consumption in this industry helps to minimize adverse environmental effects and reduce the production of greenhouse gases [3].

Despite its capacity to help with the transfer of individuals as well as goods, conveyance is vital to the modern world. The transit system uses power to operate automobiles and trains, particularly fossil-fuel energy. The demand for electricity for mobility is growing due to population and economic integration, which drives up energy consumption in this sector. It is crucial to switch to sustainable and environmentally friendly energy sources, such as electric cars and biofuels, to reduce environmental impact and assure the future of humanity [4].

Electricity is also needed for many operations in the manufacturing and agricultural sectors, such as growing crops, preparing food, wrapping, and marketing. Power must be generated to run machinery used for agriculture, keep warehouses at an appropriate temperature, and transport produce to consumers. These sectors' performance is directly connected with the price and availability of electricity. Minimizing waste, decreasing carbon dioxide emissions, and improving food availability are achievable with alternative energy methods in food manufacturing and farming.

Guidelines related to the supply of energy, dissemination, and usage are vital because of the continual availability of electrical power in every aspect of our lives. When ensuring that electricity systems are dependable, effective, and capable of evolving to satisfy future requirements, planners must consider projected assessments of energy requirements. Understanding variables influencing the generation and use of

energy, including population growth, technological advances, and environmental circumstances, is necessary for effective energy prediction [5].

Estimating energy consumption has been the main focus of most efforts in energy forecasting. However, anticipating the need for energy appears to have gotten less attention. The present research suggests using artificial neural networks (ANNs) to model energy requirements in the presence and absence of significant weather parameters and identify the appropriate statistical distribution. More precisely, the study examines meteorological factors like temperature, relative humidity, wind, cloud cover, and precipitation to investigate any relationship between these factors and the energy needs of the Indian States in future for policy making.

2. LITERATURE REVIEW

Implementation of water and energy linkage governance necessitates a more accurate assessment of the accompanying advantages and risks for every one of the nexus sectors and an examination of relationships among them, in addition to supporting unified strategic decision-making Radini et al [6]. Energy and water assets are strongly intertwined, both of which are vital for economic growth. Due to multiple unexpected difficulties, a swift rise in population and urbanization, expanding income, modernization, climate variability, and investment in the country, managing natural conditions to fulfil urban water supply and energy supply needs has become increasingly complicated. Due to the general emergence of metropolitan areas with extraordinarily huge populations in emerging regions, power and water distribution has now been dubbed the big problem for the future years by Khan et al [7].

The world's population is expected to reach nine billion by 2050, growing at an accelerated rate. Population growth, resource constraints, and climate change will harm energy generation and consumption. To address the rising energy requirements, autonomous and environmentally sustainable technologies that reduce energy use are required by Ahmad et al [8].

Different steps have been taken to use ANN to predict consistent energy consumption. Nevertheless, most investigations have aimed at improving short-term predictions, including hourly or daily predictions Hu et al [9], suggesting a data processing multimodal efficient approach and an extended short-term memory system for power prediction. Under the inclusion of time constraints and specified characteristics, it is used to forecast potential power usage. The model findings suggest

that the components of 49 business sector buildings can be used to find second-order characteristics that are substantially connected to power usage by Dai et al [10].

Another study established a revolutionary method for forecasting 510 domestic buildings' energy use for the day forward by Habbak et al [11]. A gradient-boosting clustering algorithm was used to predict the day-forward behaviour trend concept. This projected customer data group is sent through an Artificial Neural Network to increase the capture of wildly varying user actions for energy usage forecasting. They are upgrading of the existing electrical load prediction model by using appropriate input parameters such as daily thermal environment, wind velocity, and moisture content as meteorological data plus modelling techniques for the actual power load of office buildings. Their research implemented actual hourly energy information spanning 2013 to 2018 and a training sample spanning 2013 to 2017, which has been used to ensure the modelling approach was adequate. Next, a validation set consisting of the energy data from 2018 is utilized. The relative performance of hourly and daily energy forecasting for various constructions, including domestic, business, academic, and industrial spaces. They concentrated on a sophisticated ANN-based approach for the regional demand prediction model for 24 hours and 1 hour forward. The highest rating may be reached one 1hour in advance, according to the findings done by Petrosanu and Pirjan [12]. The 15-minute frequency data-driven prediction model for the day-forward electricity demand of structures. They used different evaluation assessments to determine the most influential determinants of energy usage: day type indication, duration of day, temperature scheduling, external dry heat, and external moisture. The article gives an ANN model with Bayesian performance and reliability for simple structure energy demand predictions by Kerdan and Galvez [13]. It analyzes how system design elements such as lag time, count of hidden layers, and supervised learning affect model capabilities. The experiments demonstrated that the suggested model could successfully estimate energy at 15-minute time frames and everyday maximum energy usage using adaptable learning strategies in a residential construction test set. The contributors analyzed sophisticated machine learning approaches, and this research proposes a method for estimating renewable solar electricity. The models' applicability for actual and brief solar renewable power prediction was assessed to ensure optimal protection and development needs by Adedeji et al [14]. The information they used in the investigation covers the period between 2016 and 2018. The simulations have been tested with statistics from a Moroccan territory, and they

could predict solar energy throughout both actual and short-term. The analysis used six performance measures: Mean square error, Root mean squared error, Absolute Error, R-squared, and Normalized RMSE, and assessed combined micro- and macro accuracy rates. Even if very relatively short-term projections (such as hourly or daily) as well as shorter-term projections (such as weekly or monthly) have been required for such applications they are designed for, projections with a much more extended period, including same monthly or yearly, are needed for the long-term energy resource management. Although some studies evaluated the country's socioeconomic planning and implementation's quick rise in energy consumption, it is challenging to ascertain whether a precise stochastic forecast model is trustworthy over a more extended period Wood [15], Haben et al [16]. As a result, a probabilistic concept of anticipated demand must be developed to emphasize the requirement for energy supply creation to satisfy the requirements. There are several efforts to design the fundamental probability distribution of energy time-series data using well-established methodologies such as the Generalized Extreme Value distribution (GEV), Jhonson SB distribution, Weibull distribution, Burr distribution, Kumaraswamy distribution, etc., with the best distribution function chosen based on relevant goodness-of-fit test results including the Kolmogorov-Smirnov test, Anderson-Darling test, and Chi-squared test. Therefore, regarding policy considerations, every long-term projection must incorporate combined deterministic and probabilistic features, especially for energy needs investigations.

3. RESEARCH PROBLEM

Energy is a vital asset that drives economies worldwide, keeps industries going, and helps people go about their everyday lives. Consistently estimating energy needs and availability is essential for building infrastructure, utilization of resources optimization, and security of energy supply. The necessity for trustworthy predictive models in the context of predicting energy availability and requirements is addressed in this study, which finds appropriate fits for probability distributions that can improve these forecasts' precision and dependability. The primary research problem is developing robust models to predict future energy availability and requirements. This involves Energy Availability and requirement prediction: Predicting the quantity of energy that will become accessible over a range of periods from diverse sources (such as renewables and fossil fuels), known as energy availability. Energy Requirement Forecasting: Projecting the energy consumption from different industries (such as

transportation, industry, and residential) while considering regulatory changes, economic growth, and technical developments. Identifying Suitable Probability Distributions: Selecting appropriate probability distributions To increase the accuracy of upcoming energy forecasts, the proper probability distributions that most closely match past energy data should be identified.

4. OBJECTIVES OF THE WORK

The main objectives of this research work are,

1. To determine suitable probability distributions, statistical analysis of historical energy data is performed to identify patterns and distributions.
2. To develop predictive models for energy availability by analyzing historical energy data, identifying trends, and creating statistical and Artificial Neural Network models to forecast future energy availability.
3. To develop predictive models for energy requirements by gathering data on historical energy consumption across different sectors.

5. PROPOSED METHOD

This thesis contributes towards developing long-term energy forecasting for achieving future energy needs by analyzing historical data and selecting suitable probability distribution analysis and future energy forecasting estimated by artificial neural network techniques.

Identifying suitable probability distribution

A probabilistic understanding of forecast demand should be made to prioritize creating energy supplies to meet the demands. Attempts are also there to model the underlying probability distribution of energy time series using established methods such as Generalized Extreme Value distribution (GEV), Jhonson SB distribution, Weibull distribution, Burr distribution, Kumaraswamy distribution etc. are considered. The most suited distribution function is selected based on appropriate goodness-of-fit tests such as Kolmogorov-Smirnov, Anderson-Darling, and Chi-squared tests.

Generalized Extreme Value distribution

The probability density function of a GEV distribution with parameters η, ξ and σ of a continuous random variable x is defined as

$$f(x) = \begin{cases} \frac{1}{\sigma} exp\left[-(1+\xi y_1)^{-1/\xi}\right](1+\xi y_1)^{-1-1/\xi} & \text{if } \xi \neq 0 \\ \frac{1}{\sigma} exp(-y_1 - exp(-y_1)) & \text{if } \xi = 0 \end{cases}$$

$$\text{where } y_1 = \frac{x-\eta}{\sigma}, \eta, \sigma > \quad (1)$$

Johnson SB distribution

The Johnson SB distribution of a continuous random variable x with parameters δ> 0, λ > 0, u > 0and v > 0, is defined by its probability density function as

$$f(x) = \frac{\delta}{\lambda\sqrt{2\pi}y(1-y)} exp\left[-\frac{1}{2}\left(v + \delta\, ln\frac{y}{1-y}\right)^2\right] \text{ where } y = \frac{x-u}{\lambda}, \quad u \leq x \leq u+\lambda \quad (2)$$

Kumaraswamy distribution

The Kumaraswamy distribution has the same fundamental form as the beta distribution. It resembles the Beta distribution so much that it is frequently referred to. On the other hand, the Kumaraswamy distribution is easier to use and, in some instances, more tractable. Without taking into account inflation, the Kumaraswamy distribution's probability density function is

$$f(x) = abx^{a-1}(1-x^a)^{b-1} \quad (3)$$

where x €=(0,1), as well as both a and b, are shape characteristics that are not negative.

Testing the goodness of fit

We use three different goodness-of-fit tests to find the best fit of a probability distribution for energy requirements data: the Kolmogorov–Smirnov test, Anderson–Darling test and Chi-square test at a 5% significance level. The selection of best-fit distribution is done based on the concept of minimum error.

Kolmogorov–Smirnov (K–S) Test

Kolmogorov and Smirnov discovered the Kolmogorov-Smirnov (K-S) test, and it is also one of the simple non-parametric tests used to test whether data follow a specified or assumed distribution or sample has come from a restricted or assumed distribution.

$$D = \max_x |F(x) - F_0(x)| \quad (4)$$

Anderson–Darling Test

The Anderson–Darling (A–D) test is one of the statistical tests used to test whether the sample of data is drawn from a specified or assumed distribution. In addition, this test is frequently used to find the best fit of probability distribution and parameter estimation. The test statistic for the A–D test is defined as follows.

$$AD = -n - \frac{1}{n}\sum_{i=1}^{n}(2i-1)\left(ln\,F\,(x_i) + ln\left(1 - F(x_{n-i+1})\right)\right) \quad (5)$$

Chi-square (χ2) Test

The chi-square test is one of the prominent goodness of fit tests that can be used to evaluate the relationship between two nominal or more ordinal variables. χ^2 measures the actual divergence of the observed and expected frequencies. Let us assume that the observed frequency of the sample items is O_i (i = 1, 2, ...,n) and the predicted frequency E_i(i = 1, 2, ...,n). The Chi-square test statistic is defined as follows.

$$\chi^2 = \sum\left[\frac{(O_i - E_i)^2}{E_i}\right] \quad (6)$$

Modelling Tool Artificial Neural Network (ANN)

This study uses an artificial neural network (ANN) to predict future energy requirements and availability. In ANN, concurrent neurons are present in 3 layers: input, hidden, and output. A "back-propagation" method is commonly employed and used in this research. The three-layered ANN architecture used in this study is depicted in Figure 2. The conceptual ANN model has been implemented using the NeuroShell program and is presented in Figure 3.

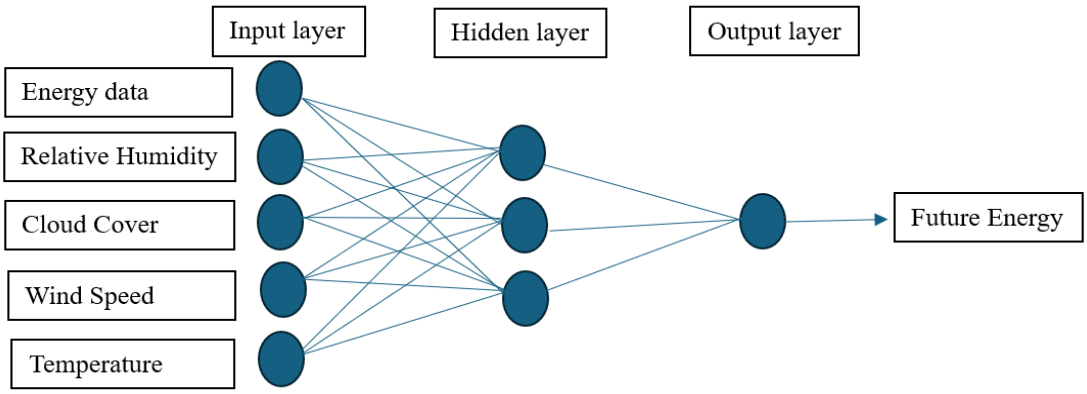

Figure 2: Overview of the conceptual ANN model

ANN is an artificial intelligence methodology based on the operation of the biological neural network. The neural network tends to store and organize knowledge

from previous experiences. As a result, the knowledge gained will be put to good use in an undetermined future scenario. Even without explicit instructions, ANN enables a computer's meaningful learning power. As a model of the human brain, ANN has many neurons that combine to analyze big data and show patterns. ANN has been most widely used for solving problems with incorrect or missing data and finding a relationship between two variables that are linked more multi-dimensionally.

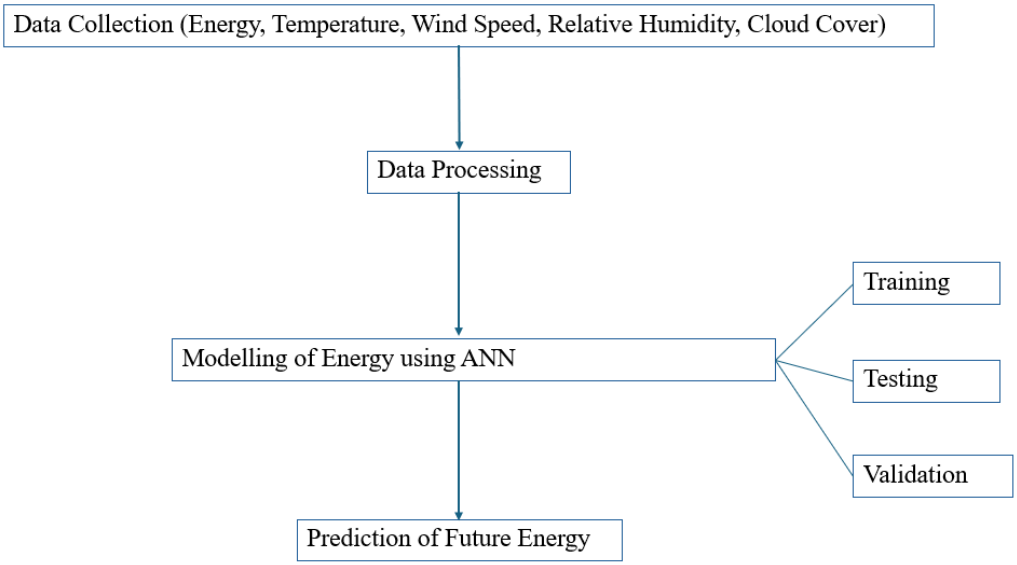

Figure 3: Overview of the conceptual ANN model

6. OVERVIEW OF THE RESULTS

Probability distributions analysis

This research assesses the recorded data of the considered study areas for the period and does a probability analysis to determine the appropriate probability fit for energy data. This study used fifteen probability distributions: the Generalized extreme value distribution (GEV), Johnson SB, Gamma 3p, Pearson 5, Frechet, Beta, Burr, Normal, Pareto, Weibull, Laplace, Exponential, Generalized Gamma and Kumaraswamy. The overall rank acquired from the abovementioned goodness-of-fit tests determines the optimum probability distribution. Each probability distribution under consideration in this study is evaluated from 1 to 10 based on the criteria that the distribution(s) with the highest total score are determined to be the best probability distribution(s) for modeling the data of a study region. Tables 1, 2 and 3 depict the descriptive statistical energy data, scale, shape and location parameters for each statistical distribution, and goodness of fit for each statistical distribution. In addition, the Probability Density Function (PDF) of the generalized extreme value pattern for energy data is shown in Figure 4.

Table 1: Descriptive statistical energy data

Sl. No.	Statistic	Value
1	Mean	745.65
2	Minimum	437
3	Maximum	1232
4	Variance	26395.0
5	Standard Deviation	162.46
6	Coefficient of Variation	0.21788
7	Excess Kurtosis	0.19252

Table 2: Scale, shape and location parameters for each statistical distribution

Sl. No.	Distribution	Parameters
1	Generalized Extreme Value	k=-0.17663; s=150.07 m=681.68
2	Generalized Gamma	k=1.0026; a=21.237; b=35.398
3	Johnson SB	g=2.9306; d=2.7752; l=2363.5; x=122.03
4	Normal	s=162.46; m=745.65
5	Weibull	a=5.5833; b=803.87
6	Gamma (3P)	a=11.828; b=47.447; g=184.46
7	Laplace	l=0.0087; m=745.65
8	Beta	a_1=1.8197; a_2=2.8675; a=437.0; b=1232.0
9	Pearson 5	a=21.04; b=14960.0
10	Ferchet	a=5.4863; b=654.98
11	Kumaraswamy	a_1=1.0; a_2=1.2; a=437.0; b=1232.0
12	Burr	k=0.01423; a=137.92; b=438.96
13	Pareto	a=1.958; b=437
14	Exponential	l=0.00134
15	Dagum	k=23.24; a=11.237; b=5.398

Table 3: Goodness of fit for each statistical distribution

Sl. No.	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Generalized Extreme Value	0.0850	4	1.4586	4	38.574	36
2	Generalized Gamma	0.0862	6	1.4257	2	27.787	12
3	Johnson SB	0.0927	15	1.4773	7	27.918	15
4	Normal	0.0938	19	1.6954	23	21.632	3
5	Weibull	0.0960	22	2.9907	35	15.415	1
6	Gamma (3P)	0.0965	23	1.5441	14	28.052	20
7	Laplace	0.0985	24	2.3174	32	36.197	32
8	Beta	0.1024	31	3.9644	37	37.333	35
9	Pearson 5	0.1144	35	2.0322	28	33.899	29
10	Ferchet	0.1712	43	6.2014	40	52.832	41
11	Kumaraswamy	0.2457	47	12.495	43	89.333	43
12	Burr	0.2718	49	26.648	47	182.84	47
13	Pareto	0.2743	50	29.437	48	205.09	48
14	Exponential	0.4517	53	55.177	52	582.26	53
15	Dagum	0.1824	34	3.2645	31	13.333	40

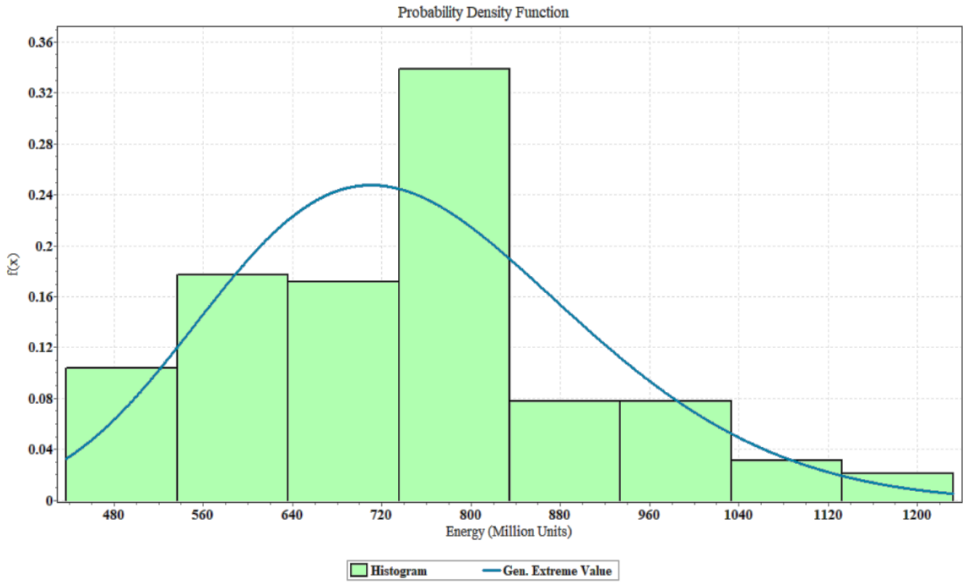

Figure 4: PDF of Generalized Extreme value pattern for energy data

Analysis of Energy availability information

This study looks at Tamil Nadu state's mean annual energy availability statistics for 23 years under four distinct scenarios. Figure 5 depicts the recorded and computed monthly energy for the availability states under consideration, while Table 4 shows the calculated statistical values.

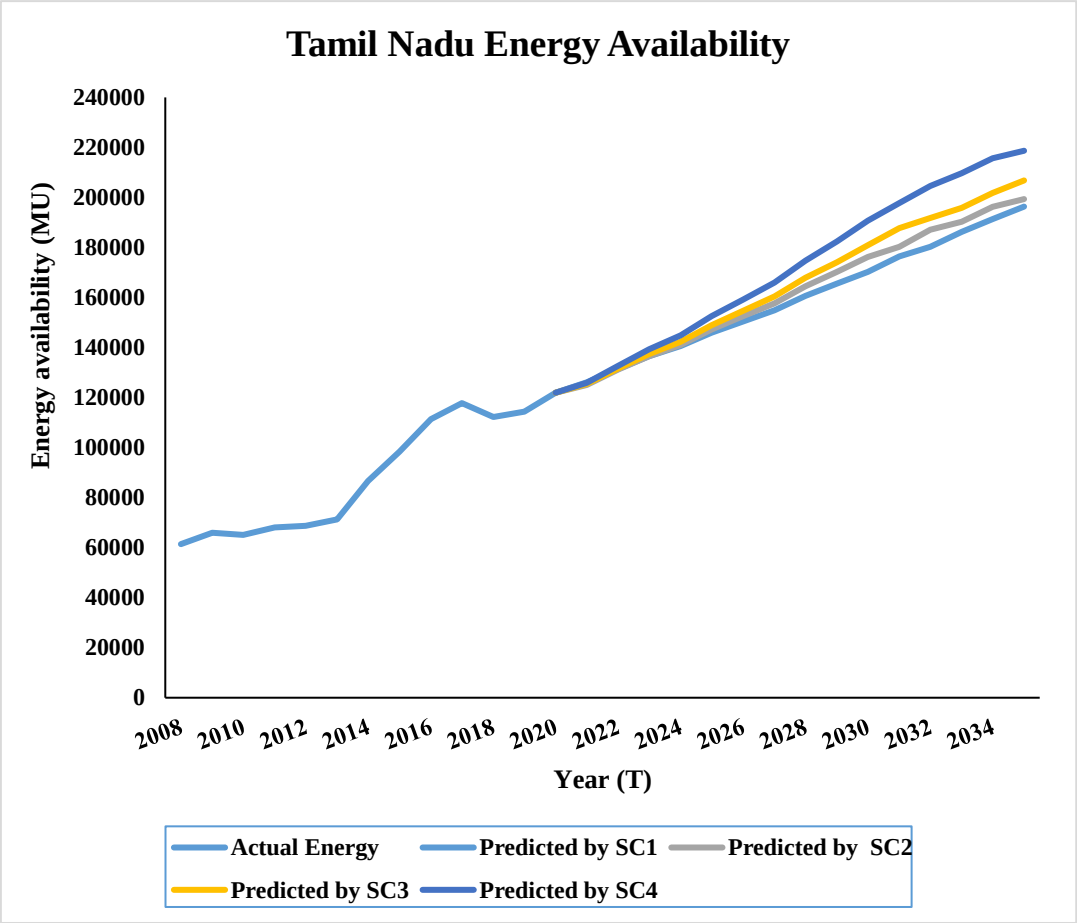

Figure 5: Trend analysis of historical and predicted energy data

Table 4: Statistical analysis of different scenarios of energy availability

Sl. No.	State	Scenario	Mini-mum (MU)	Maxi-mum (MU)	Aver-age (MU)	Skew-ness	Kurto-sis	SD
1	TN	SC1	4500	14721	9584	-0.12	-1.27	3088
		SC2	4500	15185	9657	-0.05	-1.24	3184
		SC 3	4500	15575	9734	-0.01	-1.21	3277
		SC 4	4500	16408	9896	0.10	-1.16	3477

*SD-standard deviation

Table 4 shows that the highest energy availability for the study region in 2030 under the SC4 (i.e., a 25% increase in gradient) is 16408 MU. In the same way, Tamil Nadu's minimum energy availability for 2008 will be 4500 MU. Under the SC4, a study area's average maximum energy availability is 9896 MU, whereas the average minimum energy availability is 9584 MU. We must first calculate and quantify the energy availability for the study data using the linear approximation approach and linear regression analyses. Equation (7) is used to simulate the upcoming energy availability.

$$z = ux + c \tag{7}$$

The parameter of a must be changed using the aggregated historical and predicted data, and u is the linear regression coefficient in Equation 7. Separate conditions are taken into account when constructing the equation. The total energy prediction was calculated using ANN for different scenarios, and the calculated equations are presented in Table 5.

Table 5: Calculated equations under different scenarios

S.No.	State	Scenario	Final Equation
1	Tamil Nadu	SC1	y=40.24x+4296
		SC2	y=44.42x+4296
		SC3	y=50.05x+4296
		SC4	y=51.47x+4296

7. ORGANIZATION OF THE THESIS

The structure of this thesis is organized into seven chapters, as follows:

Chapter 1

This chapter describes the motivation behind forecasting future energy requirement and their effectiveness. It also explains the importance of prediction in satisfying the various types of demand, such as industrial, agricultural, domestic, etc.

Chapter 2

A review of the works carried out by researchers with various statistical models, techniques, and methods for various energy demand and future forecasting concepts, as well as the importance of such prediction technologies with real-time data, has been reported in this chapter. The motivation behind the proposed methodology has also been defined here.

Chapter 3

This chapter discusses the various statistical distribution fit models considered for this work, such as the Gen. Extreme Value, Gen Gamma, Johnson SB, Normal, Weibull, Gamma (3P), Laplace, Beta, Pearson 5, Ferchet, Kumaraswamy, Burr, Pareto, Exponential and Dagum distribution. It also states the three distinct tests utilized to find the best fit. Different mathematical distribution fits are employed for modelling and anticipating trends, patterns, and uncertainties to predict future energy consumption.

Chapter 4

The entire procedure for creating, evaluating, and forecasting energy availability with Artificial Neural Network (ANN) models is summarized in this chapter. The objective is to tackle the existing knowledge gaps on energy availability and offer reliable projections for upcoming situations. This chapter provides insightful analysis and practical energy planning and management recommendations by thoroughly evaluating numerous scenarios.

Chapter 5

This chapter summarizes the process for developing, assessing, and forecasting energy requirements or demand using Artificial Neural Network (ANN) models. The aim is to address the current gaps in our understanding of energy requirements and provide accurate forecasts for future scenarios. This chapter thoroughly examines various potential scenarios to provide incisive analysis and valuable suggestions for energy strategy and administration.

Chapter 6

This chapter applies and implements a thorough case study emphasizing wind and hydro energy scenarios. This chapter aims to thoroughly examine the possibilities, difficulties, and consequences of these energy sources for developing and conserving energy for future generations. Data gathering, mathematical simulation, and prospect evaluation are all part of the empirical study technique, which aims to produce insightful conclusions and suggestions.

Chapter 7

This chapter concludes the dissertation's findings and discusses the subsequent research that must be done in this area.

8. CONCLUSION

Energy is a vital asset that drives economies worldwide, keeps industries going, and helps people go about their everyday lives. Consistently estimating energy needs and availability is essential for building infrastructure, utilization of resources optimization, and security of energy supply. The necessity for trustworthy predictive models in the context of predicting energy availability and requirement is addressed in this study. And find appropriate fits for probability distributions that can improve these forecasts' precision and dependability. The primary research problem is developing robust models to predict future energy availability and requirements and identifying suitable probability Distributions. In detail, the forecast of future energy requirements and exceedance probability is estimated and discussed by considering four different scenarios, from no change in trend to a 25 % increase. Statistical assessment is done for various probability distributions. It is tested by goodness-of-fit tests, namely, the Kolmogorov-Smirnov test, Anderson-Darling test and Chi-squared test to find the best probability fit. It is seen that various distinct distributions are the best fit for the study area considered. In addition, based on a rank of goodness-of-fit tests, it can be concluded that a 97 % minimum exceedance probability condition is maintained for overall states under four different conditions. It is concluded that the States will be able to meet the average energy requirement with minimal policy intervention for all the 10 % scenarios, whereas, for the other scenarios, a careful policy change may be required to create avenues for energy generation. However, there is only a 1 % to 5 % exceedance probability for the 15 % scenario. This work proposes the development of an effective forecasting model. At the first level, forecasting of energy requirements is done with energy availability as the input information. At the second level, it is desired to forecast the energy requirement with weather parameters such as temperature and rainfall as the inputs. The variation in these parameters has a significant influence on the energy requirements. The proposed models are developed for different states in India, and monthly data on energy requirements, energy availability, and weather parameters are provided for the years considered. Artificial Neural Network (ANN) is used as a forecasting tool because of its wide use and acceptance by various researchers as an effective modelling tool. It has been implemented using the Neuroshell / MATLAB platform in this study. The results indicate that the proposed ANN models can predict the energy requirements for considered states with a CC of about 0.9. The importance of considering weather parameter changes as an essential source of information for planning energy-related studies is found to be necessary.

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